“A Comparative Analysis of Deep Learning Approaches for Identifying Nutrient Deficiencies in Plants”

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Essential mineral nutrients play a crucial role in the growth and survival of plants. The lack of nutrients in plants threatens global food security and affects farmers who solely depend on producing healthy crops. Traditionally the identification of nutrient deficiencies in a crop is done manually by experienced farmers. Deep learning (DL) has shown promise in image classification. However, the lack of understanding regarding the accuracy and explainability of specific DL models for the identification of plant nutrient deficiencies is a hindrance to making informed decisions about the suitability of these algorithms for practical implementation. This study aimed to assess the performance and explainability of these models to facilitate better decision-making in agriculture.

Essential mineral nutrients play a crucial role in the growth and survival of plants, and they are required in varying quantities as macronutrients and micronutrients. Minni & Rehna (2016) state that macronutrients are nutrients that are needed in significant amounts, while micronutrients are required in smaller quantities. Potassium (K), Phosphorus (P), Sulphur (S), Nitrogen (N), Magnesium (Mg), and Calcium (Ca) are the six macronutrients that are essential for plant growth and development (Shete, Gosavi, Bulbule, Patil & Pawar, 2020). Micronutrients consist of Ferrum (Fe), Manganese (Mn), Zinc (Zn), and Cuprum (Cu) (also known as copper). In the absence of the aforementioned nutrients, plants cannot complete their lifecycle and accomplish their physiological functions (Yi, Krusenbaum, Unger, Hüging, Seidel, Schaaf & Gall, 2020)..

This study presents a novel approach in the field of agriculture by focusing on the comparative analysis of the performance and explainability of DL models in the identification of plant nutrient deficiencies. The intricacies of

the agricultural domain, including diverse plant types, seasonal variations, and environmental factors, demand transparent and understandable models.

To address this need, the study used two different plant datasets to explore the performance and explainability of DL models in identifying nutrient deficiencies in plants. By leveraging these models, the researcher aimed to uncover crucial insights into how these essential features in the data influence the prediction of nutrient deficiencies. As highlighted by Schmidt, Jensen & Husted (2016), Nutrient deficiencies can significantly impact plant growth and yield, and timely identification and correction are crucial for optimal plant performance.

1. Introduction

Human nutrition is affected by the nutritional value of plant products, whether directly or indirectly, as stated by Kihara, Bolo, Kinyua, Rurinda & Piikki (2020). Agriculture has seen the automation of various tasks through the application of image analysis techniques, including plant species identification, nutrient deficiency detection, and image-based plant disease detection, as reported by Watchareeruetai, Noinongyao, Wattanapaiboonsuk, Kha ntiviriya & Duangsrisai (2018), and Mohanty, Hughes & Salathé (2016).

Visual signs of nutrient deficiencies can be seen in several sections of the plant, particularly the leaves. Visual symptoms include altered leaf colour, necrosis, and chlorosis (Leena, 2018). The early-stage diagnosis of nutrient deficiencies is an important task. The final plant produced can be affected by nutrient shortages in plants. According to Mohanty et al. (2016), the lack of nutrients in plants threatens global food security and affects smallholder farmers who solely depend on producing healthy crops. Identifying nutrient deficiencies is crucial to ensuring that all plants are developed according to specifications for nutrients like nitrogen.

Kali (2006), published a paper in the International Encyclopedia of Education journal that first introduced the concept of DL. The fundamental idea behind DL is to use "deeper" neural networks that apply various convolutions to provide a hierarchical representation of the input. DL's automatic feature extraction from raw data is a significant advantage. Kamilaris (2018), states that DL is highly efficient and fast in solving more complex problems.

In general, DL models are complex and not easily understandable by humans. Barredo (2020) notes that the demand for transparency among AI stakeholders is increasing, particularly as black-box models are employed to make important predictions in critical situations. The absence of transparency and accountability surrounding prediction models can have disastrous results in some circumstances. XAI refers to techniques for obtaining the intelligible output of an ML model and presenting it in a manner that is understandable to humans (Gerlings, Shollo & Constantiou, 2021). Páez (2019), highlights that one of the crucial objectives of XAI is to establish trust in the model. ML models need to provide not only output but also understandable explanations behind the rationale of the machine.

The identification of plant nutrient deficiencies through the implementation of ML techniques has been explored in the existing literature such as Tran, Choi, Le & Kim (2019). However, there is still a significant research gap in the comparative analysis of the explainability of DL models in identifying nutrient deficiencies in plants. While some studies have looked into the use of ML for this purpose, there has not been much research done on the effectiveness and potential benefits of using explainable DL. Addressing this gap is essential to gaining a comprehensive understanding of the most effective and explainable approach for nutrient deficiency identification in plants.

2. Review of Literature

The following literature review provides an overview of the use of deep learning for plant nutrient deficiency identification.

Watchareeruetai, Noinongyao, Wattanapaiboonsuk, Khantiviriya & Duangsrisai (2018) proposed a method that uses CNNs to identify plant nutrient deficiencies, including Mg, Ca, and N, among others. The proposed experiment was conducted on a set of black gram plants. To assess how well the experiment performed, the researcher compared the results with two trained humans. Compared to the two people's accuracy performance (27.37%), the proposed model performed with 43.02% more accuracy. The experiment revealed that if there are diverse types of nutrients to identify, it becomes difficult to accurately identify the nutrients.

Tran, Choi, Le & Kim (2019) accurately predicted nutrient deficiencies to increase crop production and prevent tomato pathology caused by a lack of nutrients such as Calcium, Nitrogen, and Potassium. Noon, Amjad, Qureshi & Mannan (2020) conducted a review of 45 DL techniques proposed for 33 different crops using 14 well-known convolutional neural architectures. Meanwhile, Xu, Guo, Zhu, He, Zhao, Han & Subedi (2020) explored the accuracy of various DCNNs for diagnosing nutrient deficiencies in rice. Abade, Ferreira & Vidal (2020) conducted a systematic review of the literature to determine the current state of the art in using CNNs for identifying and classifying plant diseases. Their findings demonstrate the potential of DL, particularly CNNs, in the field of agriculture and plant disease detection, while also highlighting trends and gaps in the research.

The performance of palm leaf nutrient deficiency detection using CNN was evaluated by Ibrahim, Hasan, Sabri, Abu & Rahimi (2022) through a confusion matrix. The results showed an overall mean accuracy of 94.29%, a sensitivity of 80%, and a specification of 96.67%. Another vision-based monitoring system was proposed by

Claudio (2020). The experiment aimed to identify tomato plants that were deficient in the main nutrients such as nitrogen. Furthermore, the implementation of such systems can increase the quantity and quality of plants. The proposed CNN model had an accuracy rate of 86.57%. Zeng, Song, Li, Chusap & Liu (2021) introduced a human-in-the-loop method that utilises verbatim neighbourhood manifestation to explain ML models. Similarly, Veldhuis, Ariëns, Ypma, Abeel & Benschop (2022) draw on XAI techniques in their 2022 study to aid users in comprehending the reasoning behind particular predictions.

Rodrigo (2020) addressed the issue of CNN-based solutions' lack of explainability by utilizing the CNN model and YOLOv3 to generate easily understandable outcomes for nutrient deficiencies. During the study, the model was trained to detect nutrient deficiencies in lettuce, specifically nitrogen, magnesium, and calcium. The training data resulted in a mean average precision of 94.38%. In a similar vein, another author Humaion, Salman, Shafi, Samanta, Rabeya & Mehedi (2022) used three pre-trained CNN models to detect plant leaf disease. Among the three models, EfficientNetV2L demonstrated a remarkable accuracy of 99.63%. To explain the predictions made by EfficientNetV2L, the author used the classification XAI framework LIME.

In their 2022 study, Wei et al. (2022) delved into the interpretability of DL models across various agricultural classification tasks. Their findings indicate that the ResNet model outperformed all other models with an accuracy of above 99.11% in all experiments conducted. Additionally, the study compared three visualisation methods and concluded that the GradCAM method is the most appropriate for agricultural classification tasks.

Rakesh and Indiramma (2022), focus on the use of the DL model with XAI for crop disease detection. The experimental results show that both Inception-V3 and ResNet-9 achieved high accuracy, 98.18% and 99.2% respectively. The study showcases the potential of XAI in enhancing the transparency of DL models. Additionally, the author employs XAI tools such as LIME and Grad-CAM to offer visual interpretations for the model's predictions.

Ghosal, Blystone, Singh, Ganapathysubramanian, Singh & Sarkar (2018) show the capability of DCNN to recognise and categorise a variety of foliar stressors in soybean. By studying more than 25,000 photos, the researcher was able to accurately identify and categorise several diseases and nutritional deficiencies. The availability of a reliable and fast explainable model would significantly impact both scientific research and agricultural production. To evaluate the nitrogen content of wheat, the researchers Singh, Roy, Setia & Pateriya (2021) suggested using machine learning and XAI. Six machine-learning regression models were used by the author to forecast the nitrogen of wheat. The gradient-boosting regression and random forest combination outperformed (□2> 0.85) previous combinations. To provide local and global explanations, SHAP values were used. According to Singh et al. (2021), based on the findings, it appears that using XAI as a tool to explain machine learning models is a promising idea.

Additionally, most of the previous research assesses the accuracy of the DL models, but they do not consider the explainability of the models. While some related work considers XAI techniques, they do not compare the different XAI techniques to understand how these models arrive at their predictions. Therefore, an integrated approach that considers both performance and explainability is lacking in the existing

body of work. This study seeks to fill the gap by comparing the explainability of two prominent XAI techniques, GRAD-CAM, and Shapley Additive explanations.

3. Problem Statement

Deep learning (DL) models' inability to provide sufficient justification is what leads to the models being called black boxes. According to Rudin (2019), several ML model predictions cannot be understood by humans due to their nature of being a black box. According to Sparrow, Howard & Degeling (2021), we need to understand why the machine-learning model performs the way it does.

According to Barredo (2020), practical implementation of explainability is imperative. However, it is currently one of the main barriers to AI. In some cases, not understanding model predictions may result in financial losses. The lack of understanding regarding the accuracy and explainability of specific DL models hinders researchers from selecting the appropriate algorithm for detecting nutrient deficiencies in plants.

The lack of understanding regarding the accuracy, and explainability of specific DL models for the identification of plant nutrient deficiencies is a hindrance to making informed decisions about the suitability of these algorithms for practical implementation.

4. Motivation

Agriculture is a cornerstone of global food security, and the health of crops directly influences the productivity and livelihoods of millions of farmers worldwide. Essential mineral nutrients play a pivotal role in ensuring robust plant growth and yield. However, nutrient deficiencies in plants are a growing challenge, impacting crop health and threatening global food supplies. Farmers, especially in

resource-limited regions, often rely on manual observation and expertise to identify these deficiencies, which can be time-consuming, subjective, and prone to errors.

Recent advancements in Deep Learning (DL) offer an opportunity to revolutionize agricultural practices through automated and precise identification of nutrient deficiencies using plant imagery. Despite this promise, a significant barrier remains: the limited understanding of how well DL models perform and the lack of explainability in their decision-making processes. For such technologies to gain the trust of farmers and agricultural practitioners, models must not only be accurate but also interpretable.

The motivation for this study stems from the urgent need to bridge this gap by evaluating and improving both the accuracy and explainability of DL models for identifying plant nutrient deficiencies. By incorporating explainable artificial intelligence (XAI) techniques, the study seeks to demystify the inner workings of DL models, enabling stakeholders to understand and trust these systems. This is particularly crucial in agriculture, where decisions based on AI models can have far-reaching implications for crop health, farmer livelihoods, and food security.

This research aims to contribute to the field by providing actionable insights into selecting and implementing DL models that balance accuracy and explainability, fostering a deeper understanding of their applicability in real-world agricultural scenarios. By doing so, the study aspires to empower farmers and agricultural stakeholders with reliable, interpretable tools for ensuring crop health and optimizing agricultural productivity.

5. Research Question

The main research question is:

RQ1: What is the relative performance and explainability of deep learning algorithms when applied to plant nutrient deficiency?

Some sub-research questions were formulated to enable the answering of the main research question. These are:

RSQ1: What are the features essential to determine plant nutrient deficiencies?

RSQ2: What are the requirements of explainable deep learning for plant nutrient deficiencies identification?

RSQ3: How can explainable deep learning be applied to a plant image dataset for plant nutrient deficiency identification?

RSQ4: What is the rating of the performance and explainability of selected deep learning algorithms for plant nutrient deficiency identification?

6. Aim of Research

The aim of this research is to develop a comprehensive understanding of the performance and explainability of deep learning models for identifying plant nutrient deficiencies using image datasets. By integrating explainable artificial intelligence (XAI) techniques, the study seeks to evaluate the accuracy and interpretability of selected deep learning algorithms, enabling informed decision-making and fostering trust in their application to agricultural practices. Ultimately, the research aims to contribute to the advancement of AI-driven tools for sustainable and efficient crop health monitoring.

7. Objectives of Research

To achieve the aim of this study, the following objectives were formulated:

1. To identify the features those are essential to determine plant nutrient deficiencies.
2. To determine the requirements of explainable deep learning for nutrient deficiency identification.

3. To explore how explainable deep learning could be applied to a plant image dataset to identify plant nutrient deficiencies.
4. To determine the performance of selected deep learning algorithms when used for plant nutrient deficiencies and their explainability

8. Research Methodology

Research design, according to Robinson (2015), is the road map for data collection, measurement, and analysis. Robinson (2015) states that there is not a single design that works in every situation. Each researcher must develop his or her design. Naturally, a variety of factors will influence the design(s) you choose. These include your research goal, its timetable, its methodology, and the data's accessibility (Håkansson, 2013). Figure 1 illustrates the experimental research design of this study. According to McNabb (2010), Experimental design (ED) is a process of designing, conducting, and evaluating the results of all types of experiments.

Research design is necessary because it makes it easier for various research activities to go smoothly, which maximises the amount of information that can be obtained with the least amount of time, effort, and money (Kothari, 2004).

Additionally, according to Robinson (2015), a significant factor affecting the validity of the obtained result is the research design. However, how any of these can be accomplished largely relies on the research purpose.

The experimental design was selected for this study because it is essential for the development and implementation of ML algorithms and models. By carefully planning, implementing, and analysing the results of experiments, researchers can ensure the validity and reliability of their findings and can make confident conclusions about the research question or hypothesis under investigation.

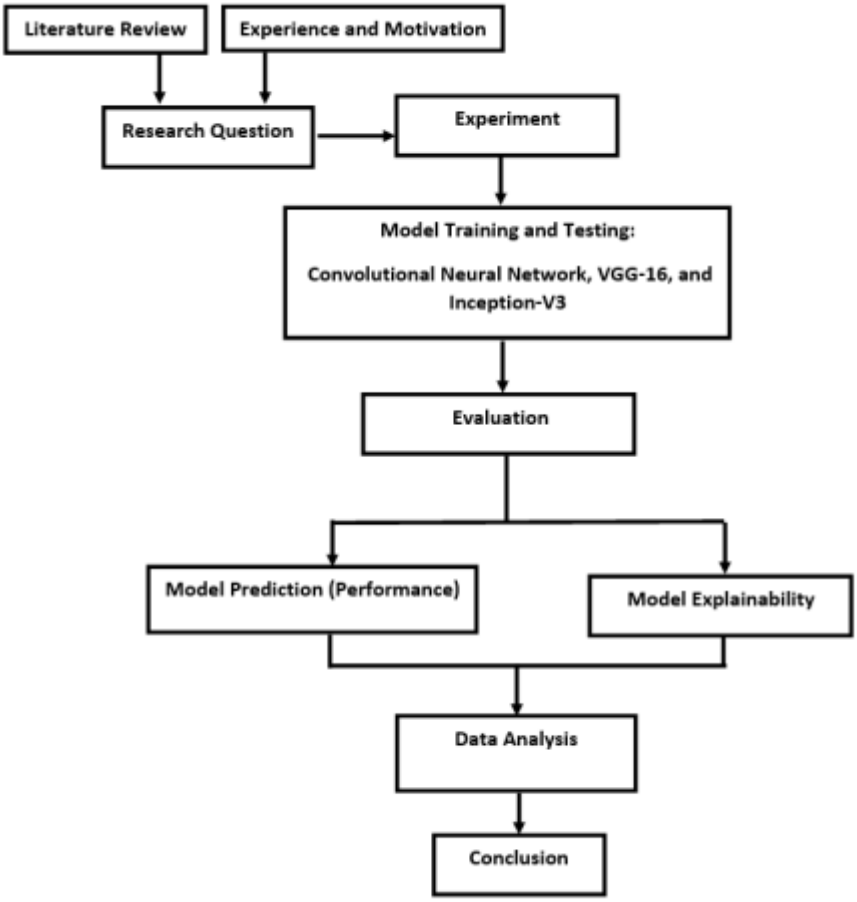

Figure 1: ***Overview of the experimental design of this study***

9. Research Significance

The research has multiple benefits for various stakeholders. Firstly, it can aid plant health professionals in identifying nutrient deficiencies in plants, simplifying their work. Secondly, farmers can use the research findings to identify nutrient deficiencies that may be affecting their crop yield and quality, enabling them to make informed decisions based on the data. Additionally, the study's findings can contribute to the body of literature, benefiting academics and upcoming researchers. The research offers new methods of using XAI in agriculture, adding value to the existing literature.

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